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## 14. ABSTRACT

The research focused on improvements in diagnosis and prognosis of crack detection through extensive use of probabilistic techniques. A unique feature of the research is that it identifies the material properties relevant to damage propagation at the same time that it performs diagnosis and prognosis. As such, it has the potential of turning aircraft into *flying fatigue laboratories* and contributing to substantial improvements in the accuracy of aircraft *digital twins*. Specific accomplishments are include the development of frequency-wave-number migration technique, image-segmentation technique, use of Bayesian techniques for combining sensors and actuators, and for narrowing down uncertainty in material properties that govern crack propagation. Together, the research is expected to substantially advance research into making structural health monitoring practical for Air Force aging planes.

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**FINAL REPORT**

Title: Probability-Based Integration of Structural Health Monitoring into the Aging Aircraft Sustainment Program
Program Manager: Dr. David Stargel and Dr. Victor Giurgiutiu (Now at U. South Carolina)
Principal Investigators: Raphael T. Haftka, University of Florida, and Fuh-Gwo Yuan, North-Carolina State University.
Investigator: Nam-Ho Kim, University of Florida.
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**Overall view:** The research focused on improvements in diagnosis and prognosis of crack detection through extensive use of probabilistic techniques. A unique feature of the research is that it identifies the material properties relevant to damage propagation at the same time that it performs diagnosis and prognosis. As such, it has the potential of turning aircraft into *flying fatigue laboratories* and contributing to substantial improvements in the accuracy of aircraft *digital twins*. Specific accomplishments are listed below. Item 1 was needed to improve accuracy, item 2 to improve image sharpness, and item 3 to take full advantage of multiple pairs of sensors of actuators. Together they provide more accurate diagnosis. Item 4 is the realization of the flying fatigue laboratory concept, and item 5 provides an efficient method that extracts maximum accuracy in prognosis from the narrowed down material properties. Item 6, which provides experimental investigation of our approach, and item 7, which looks to improve diagnosis based on prognosis, were started under the project and completed later.

Together, the research is expected to substantially advance research into making structural health monitoring practical for Air Force aging planes.

**Specific Accomplishments:**

1. Developed a frequency-wave number (f-k) migration technique for imaging the damage in a plate with the through-the-thickness crack.

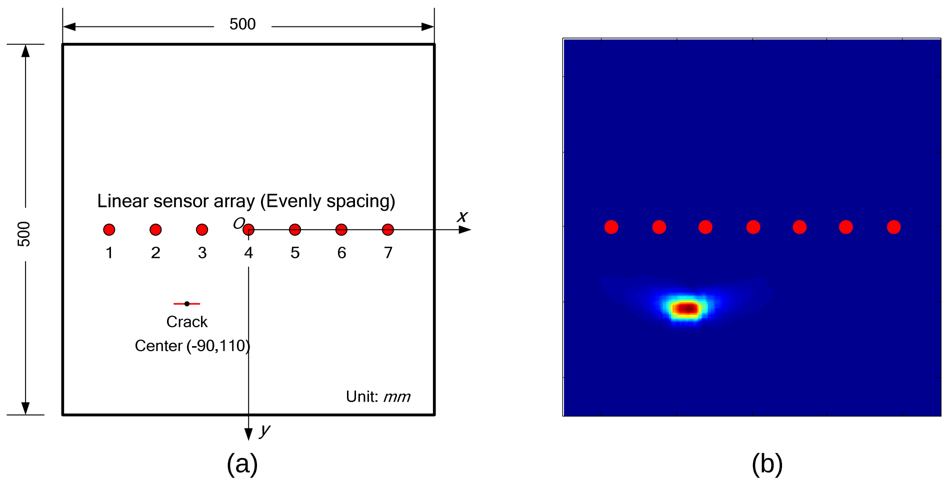



Figure 1(a) Geometry of f-k migration simulation and (b) damage image with a single crack

2. Developed an image segmentation technique, whose framework is shown as in Figure 2, for quantifying the damage size in damage image, as shown in Figure 3, using Markov Random Field and Bayesian statistics.

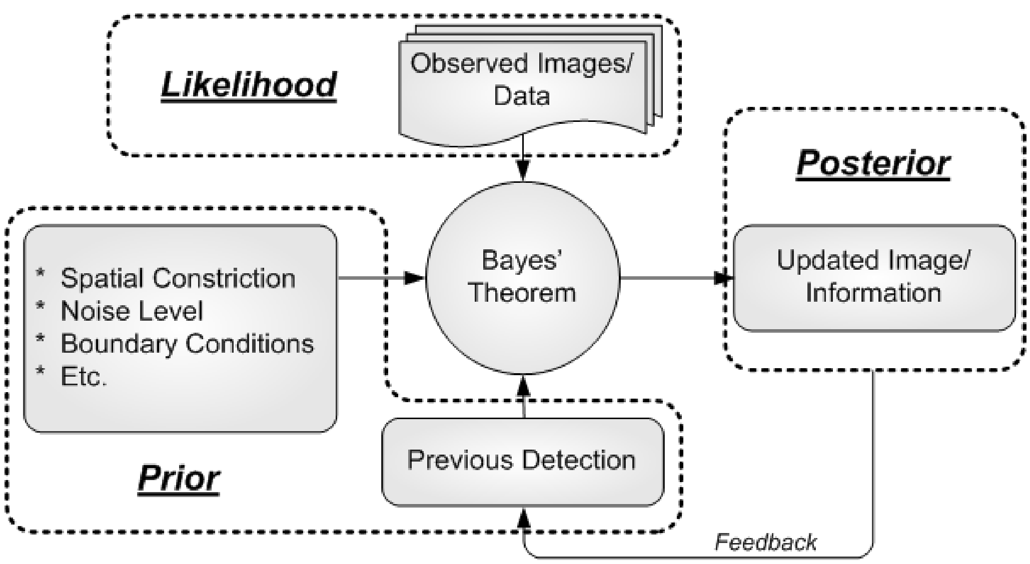
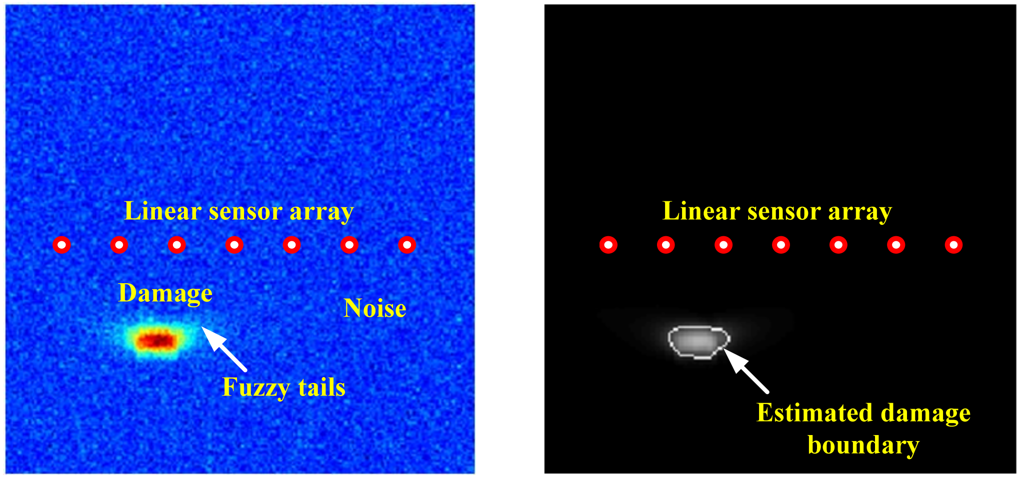



Figure 2. Framework of Bayesian based image segmentation.



(a) (b)
Figure 3 (a) An image by f-k migration and (b) the Bayesian based segmentation

The developed damage segmentation is tested at different locations in the plate corresponding to the fixed sensor array. The estimated damage sizes and damage locations by Bayesian based image segmentation method are listed in Table 1.

Table 1 Center location and damage size for multi-location simulation (Unit: *mm*)

| Crack Index | True values | | Estimated values | |
|---|---|---|---|---|
| | Size | Location | Size | Location |
| d1 | 20 | (0,80) | 27.5 | (0,80) |
| d2 | 20 | (60,80) | 25 | (60,80) |
| d3 | 20 | (120,80) | 22.5 | (117.5,80) |
| d4 | 20 | (0,110) | 27.5 | (0,110) |
| d5 | 20 | (60,110) | 27.5 | (57.5,110) |
| d6 | 20 | (120,110) | 22.5 | (117.5,107.5) |
| d7 | 20 | (0,140) | 27.5 | (0,140) |
| d8 | 20 | (60,140) | 25 | (57.5,137.5) |
| d9 | 20 | (120,140) | 22.5 | (117.5,137.5) |
| d10 | 20 | (0,170) | 27.5 | (0,170) |
| d11 | 20 | (60,170) | 22.5 | (57.5,167.5) |
| d12 | 20 | (120,170) | 22.5 | (117.5,167.5) |

3. Created a 3-step procedure, as shown in Figure 3, to extract distribution of damage size from f-k migration imaging results, and introduced gradient prior to achieve a probability density function of damage size with high confidence. The distribution from the 3-step procedure and the ones enhanced by gradient prior are given in Figure 5. Table 2 shows the estimation of most possible damage size, the average damage size in the images and their standard deviation.

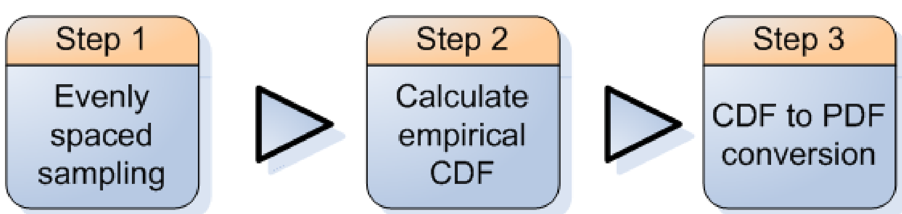
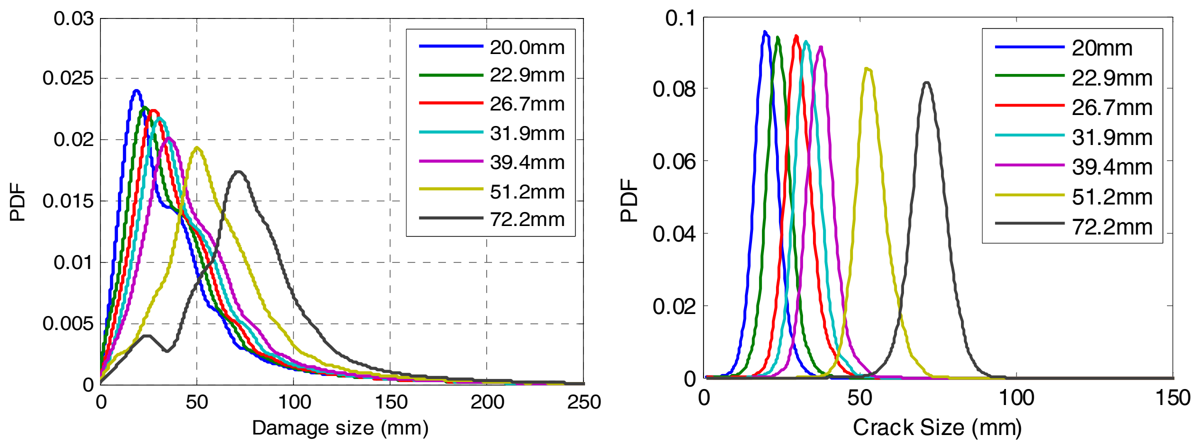



Figure 4 3-step procedure proposed to extract PDF of damage size.




(a) (b)

Figure5 (a) Extracted PDFs of damage size by 3-step procedure and (b)distribution improved by gradient prior.

Table 2. Statistical properties of distribution with gradient prior (Unit: mm).

| True | Max PDF | Mean | STD |
|---|---|---|---|
| 20 | 21.8 | 21.9 | 3.06 |
| 22.88 | 23.6 | 23.9 | 3.28 |
| 26.68 | 27.8 | 27.8 | 3.84 |
| 31.87 | 32.8 | 33.0 | 4.23 |
| 39.39 | 36.8 | 36.9 | 4.68 |
| 51.2 | 51.0 | 51.0 | 4.92 |
| 72.19 | 72.1 | 72.1 | 5.02 |

**4. Develop Bayesian updating to progressively narrow the uncertainty in damage growth parameters in spite of noise and bias in sensor measurements. Figure 6(a)**

The objective of this task is to use SHM data to predict the remaining useful life (RUL) using physics-based prognosis techniques, which incorporate the measured data into a damage growth model to predict the future behavior of the damage. Although this prediction shows acceptable estimate in the laboratory environment, it becomes challenge in practice due to uncertainty in SHM measurement process. Sources of uncertainty are from initial state estimation, current state estimation, failure threshold, sensor measurement, future load, future environment and models. This task focuses on uncertainties in sensor data, which can be classified into two categories: systematic departure due to bias, and random variability due to noise. The former is caused by calibration error, sensor location and device error, while the latter is caused by measurement environment. The major challenge in SHM-based prognosis is how to accurately predict the damage growth when the measured data include both noise and bias.

In physics-based prognosis, the damage grows according to the parameters in the physics model. The generic materials often show wide distribution of these parameters due to variability in manufacturing process and aging. However, the panel that is equipped with SHM systems may have specific damage growth parameters. The main objective of this task is to demonstrate the reduction in uncertainty of these parameters using an abundance of SHM data, although they include noise and bias. In other words, numerous data obtained from SHM can be used to characterize damage growth behaviors of a specific structure. A statistical approach using Bayesian inference is employed to progressively improve the accuracy of predicting damage growth parameters under noise and bias of sensor measurements.

The proposed approach is demonstrated using a through-the-thickness crack in an aircraft fuselage panel which grows through cycles of pressurization. A simple Paris model with two parameters is utilized. However, more advanced models can also be used, which usually comes with more parameters. Using this simple model, the goal is to demonstrate that noisy SHM data can be used to identify the damage growth parameters of the monitored panel. This process can be viewed as turning every aircraft into a flying fatigue laboratory. Reducing uncertainty in damage growth parameters can reduce in turn the uncertainty in predicting RUL; i.e., prognosis. Improved knowledge of RUL can have practical consequences such as increased time between visual inspections, or a reduction in hardware testing when SHM is combined with manual inspection.

Since there is real aircraft that equipped with SHM system, synthetic measurement data are used in this study. First, it is assumed that the panel has specific damage growth parameters ($m_{true}$ = 3.8 and $C_{true}$ = 1.5E-10) for the Paris model. It is also assumed that the damage assessment using SHM is performed every 100 flights. In practice, this can be done every flight. Then the 'true' damage grows as a function of the number of flights following the Paris model with the true values of parameters. At each assessment cycle, random noise and deterministic bias in the SHM process are added to the true damage size, which is then called the 'measured' damage size. These measured damage sizes are used to estimate the damage growth parameters (m and C). The accuracy of estimate can be evaluated by comparing them with the true ones ($m_{true}$ and $C_{true}$).

As a first step, it is assumed that $C_{true}$ is known and only m is unknown. This assumption is taken to show how the Bayesian process effectively identifies damage growth parameters. Figure 6(a) shows a case when bias is equal to zero and noise is uniformly distributed between -1mm and 1mm. The initial distribution of m starts from a uniform distribution between 3.3 and 4.3, which was estimated from test article. It can be found that the distribution of m was quickly narrowed and converges to the true value. It was observed that the initial convergence rate is slow, but gradually accelerated as the size of damage increases. This is expected because as damage grows quickly, the ratio between noise and signal becomes smaller. Table 1 summarized the identified damage growth parameter m under various combinations of noise and bias. It can be observed that a large noise can cause a large uncertainty in the parameter, while the positive bias can cause underestimation of the parameters. As a whole, however, the Bayesian process identifies the damage growth parameter fairly accurate with a very small level of uncertainty. Similar results have also been obtained for the case when the parameter C is unknown.

Table 1: Statistical characteristics of final PDF of m with different combinations bias/noise

| | Effect of noise | | Effect of bias | |
|---|---|---|---|---|
| Bias, noise (mm) | $b$ = 0, $V$ = 1 | $b$ = 0, $V$ = 3 | $b$ = -2, $V$ = 1 | $b$ = +2, $V$ = 1 |
| Max. likelihood | 3.80 | 3.80 | 3.82 | 3.78 |
| Mean | 3.80 | 3.80 | 3.82 | 3.78 |
| Standard deviation | 0.01 | 0.04 | 0.01 | 0.01 |

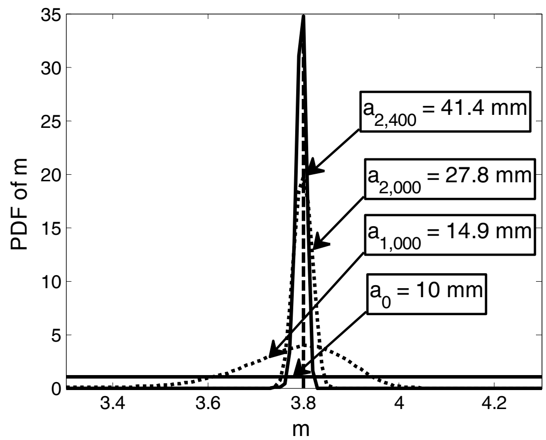
Once uncertainty in damage growth parameters are identified, they can be used to predict the remaining useful life (RUL), which is the life before the damage grows to the critical damage size. There are several uncertainties involved in predicting RUL: the current measured damage size, damage growth parameters, and loadings (i.e., pressure differential). Since the uncertainty in damage growth parameters in early cycles is large, the uncertainty in RUL will also be large. However, this uncertainty is expected to be reduced according to that of damage growth parameters. In order to have a safe prediction of RUL, the 5th percentile RUL is used as a conservative estimate of RUL. Since synthetic data are used by adding random noise, the result may vary with different sets of data. Thus, the above process is repeated with 100 sets of data, and 68% confidence intervals are plotted. Figure 3(b) shows these conservative intervals of RUL. In order to compare the predicted RUL with true one, the true RUL is also plotted in the figure. Note that initially the difference between the true and predicted RULs is significant because uncertainty is large at an early stage. However, the predicted RUL converges to the true one from the safe side as more numbers of updates are performed. In addition, the variability of estimated RUL is also gradually reduced. Thus, it can be concluded that the proposed Bayesian inference can estimate panel-specific damage growth parameters as well as the RUL while maintaining conservative.

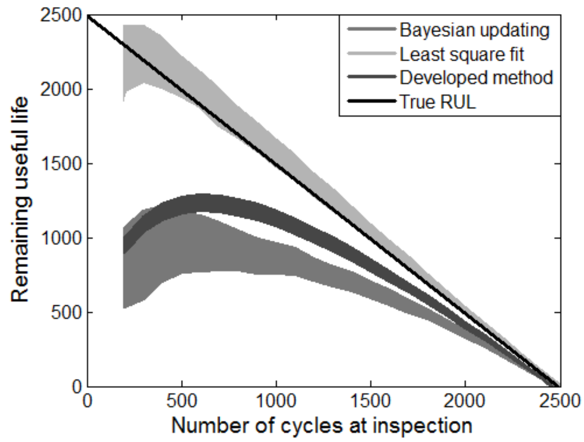
**5. Developed a probabilistic model for damage size distribution from the damage imaging and estimated the distribution of remaining useful life (RUL) using a combination of Bayesian updating and least squares fitting of damage growth parameters.**

In the previous research, the Bayesian method has been used for progressively reducing the uncertainty in structure-specific damage growth parameters in spite of noise and bias in sensor measurements. However, Bayesian updating is computationally intensive and may not be feasible to use with an extremely large number of measurements. Least-squares method, on the other hand, is efficient, but does not provide good statistical information on the uncertainty in their estimates and in RUL estimates. In this research, we propose combining the two approaches by using the least-squares approach to filter data for the Bayesian updating.

Least square fit is the easiest and most commonly used way of identifying model parameters by minimizing the difference between measured data and predicted data from the physics model. In our application, the Paris model is used with the following unknown parameters: initial crack size, damage growth parameter, and bias. The parameter C is still assumed to be known in order to compare with the results in the previous research. Although the Bayesian method is performed at every 100 cycles, the least-square-fit is performed at every cycle because the accuracy of fitting is better with more data. Similar to the Bayesian method, the identified parameters depend on synthetic measurement data. Thus, 1,000 sets of measurement data are produced by adding deterministic bias and random noise to the true crack sizes. Thus, at every measurement cycle, there exist 1,000 identified parameters, from which the distribution of parameter is estimated. By following the same procedure with the Bayesian method, the distribution of conservative RUL is plotted in Figure 3(b). It can be observed that the least-square method yields narrower distribution of RUL, but the distribution of 5th percentile can be unconservative compare to the true RUL.

Both Bayesian updating and least square fit present advantages and limitations, but they appear to be complementary. Least square fit ability to identify the bias and reduce the noise makes it a useful tool to process the data in order to identify the distribution of RUL using Bayesian updating. In order to combine the advantages of the two methods, we propose to process information collected at every cycle by least square fit in order to reduce the noise, and identify the bias. The filtered data is then used in Bayesian updating in order to narrow down the distribution of m and obtain a more accurate prognosis. It was observed that the proposed method rapidly converges to the accurate damage parameters. Fairly accurate damage parameters can be obtained also with measurement errors of 5mm. Using the identified damage parameters, it is shown that the 95% conservative RUL converges to the true RUL from the conservative side (See Figure 3(b)).



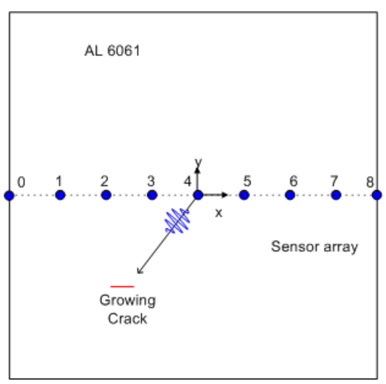



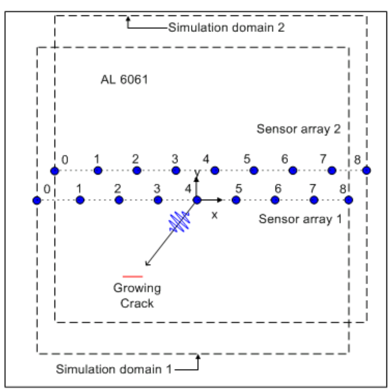

(a) (b)

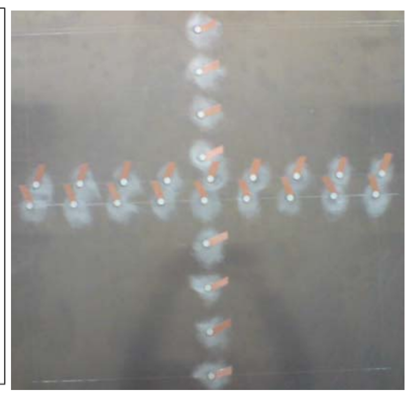
Figure 6 (a) A very wide initial distribution of the exponent in Paris law for crack growth is successively narrowed as crack measurements accumulate(b) By combining Bayesian updating and least squares identification of crack growth, the

## 6. Experimental Study on Identifying Cracks of Increasing Size using Ultrasonic Excitation

The objective of this task is to explore the relationship between the sensor signal amplitude and crack size through experiments and simulation for estimating the size. The equally-spaced sensor arrays are attached to the plate as shown in Figure 1(c). The two sets of linear arrays are used to study the effect of crack location. When a PZT disc is used as an actuator, all other PZT discs in the array are used as sensors.



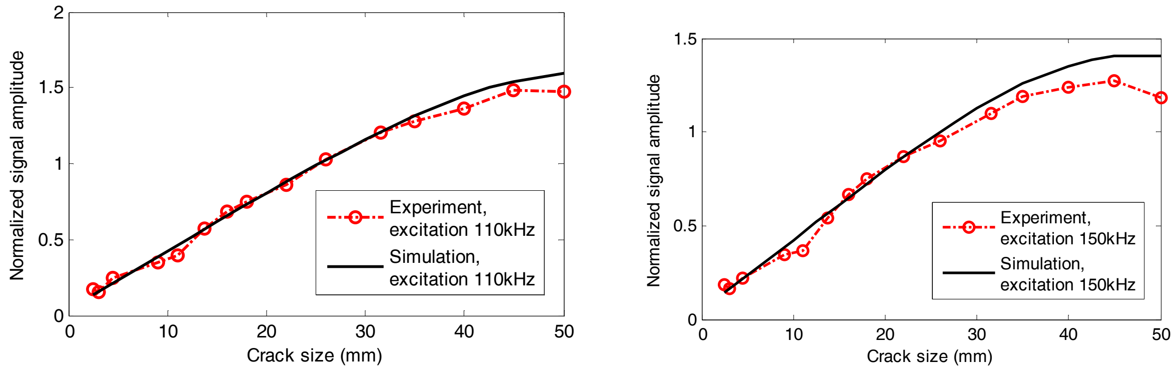



(a) (b) (c)

Figure 7. Layout of actuators and sensors (a) One set of sensors for simulation and experiment (b) Two sensor arrays attached to the plate and their corresponding domain (c) Aluminum 6061 test plate – pristine state. Three arrays of sensors are attached to the plate, but the vertical array is not employed in this research.

Cracks are machined into an aluminum plate and measurements are carried out with ultrasound excitation using piezoelectric transducer arrays that alternate their role as actuators or sensors. Initially, a hole of 2.5mm diameter is drilled in the plate, and it is gradually machined to a crack with a size up to 50mm.  Signal amplitude is measured from the sensor arrays.




(a) (b)

Figure 8 Signal amplitude variation (maximum peak-to-peak amplitude). The excitation frequencies are (a) 110 kHz and (b) 150kHz, and the signal amplitude is normalized using the signal at crack size 25 mm as the reference.

Figure 8 shows the result of this experiment. The maximum received signal amplitude is found to vary linearly with size from simulation and this agrees with measurements with crack size up to 30 mm. With different excitation frequency, the comparison between simulation and experiments shows substantial difference in terms of size estimation capability. Generally higher frequencies are able to detect smaller cracks, but also are sensitive to the shape of the crack tips so the larger size is often misinterpreted when high frequency excitation is used.

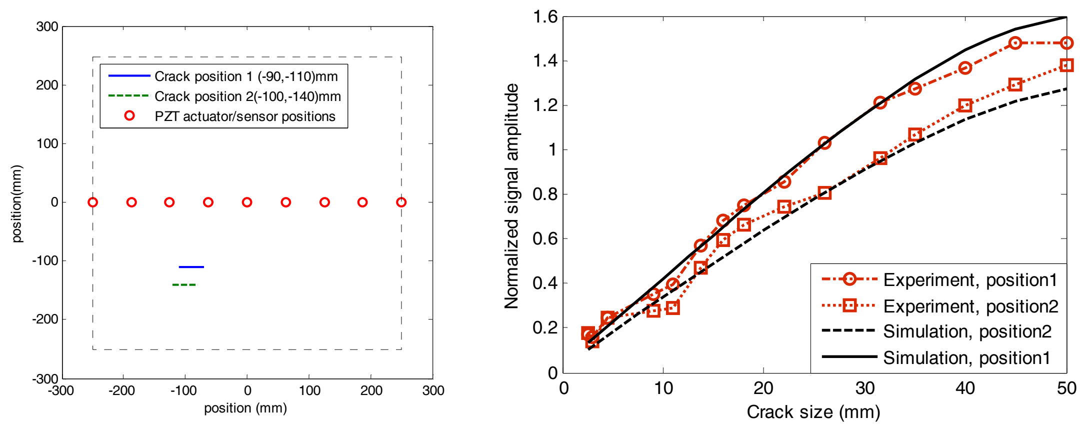


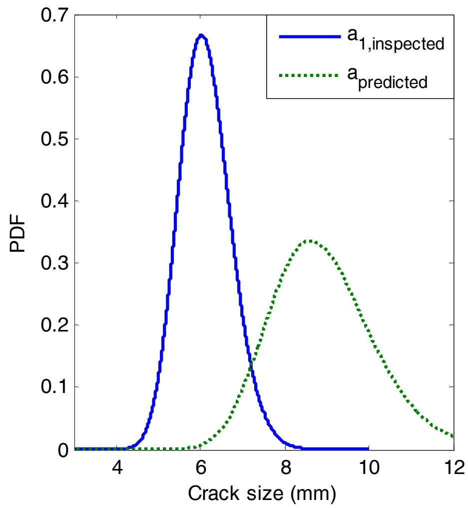

Figure 9. Scattered signal amplitude variation for cracks growing at a different location excited by 110 kHz ultrasonic toneburst. Signal amplitude comparison with result shown in Figure 11, simulation and experiment.

We next investigated the effect of the relative location of the crack and the sensor array. The crack is located at (-90mm, -110mm) from sensor 4 of array 1, while it is located at (-100mm, -140mm) from sensor 4 of array 2 (Figure 9b). The behavior of maximum signal amplitude is predicted by simulation, and obtained from experiment. By using sensor array 2, we were able to obtain the signal amplitude for crack position 2, and compared it with the simulation results in Figure 9b. Since the distance from the sensor array is larger, the slope of peak-to-peak amplitude to the crack size is smaller compared to the previous experiment, but slightly larger than expected from the simulation.

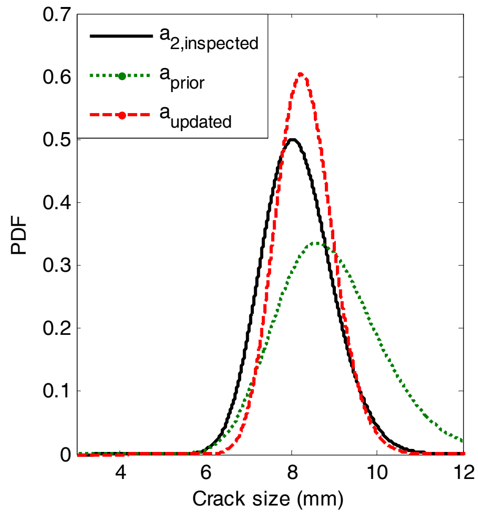
This work utilizes signal amplitude to measure crack sizes. We have shown that the increasing signal amplitude can indicate crack propagation. This approach may provide a useful inference about a small crack, whose size is difficult to measure with other techniques.

## 7. Improving Diagnosis from Past Prognosis

In the previous research, the increment of the crack size can be found by analyzing sensor signals. Considering the nature of noisy environment condition we have to face with an actual implementation of SHM system, this work aims for further accuracy on the diagnosis using past prognosis information. Unlike manual inspection, SHM can take frequent measurements and trace crack growth. By taking advantage of this fact, higher accuracy about current crack size can be achieved. First, using the previous SHM measurements and the crack propagation model, we predict statistical distribution of crack sizes at the next SHM inspection cycle. Then, this predicted distribution is combined with the SHM measurement at the next cycle by using the Bayesian approach for more precise measurement (Figure 10). That is, the propagated distribution from the previous inspection is used as a prior and the variability at the current inspection is used to build the likelihood function.



(a)



(b)

Figure 10. Simulation procedure (a) Measurement probability distribution and predicted probability distribution of crack size after 2500 cycles (b) Predicted distribution is used as a prior for the next inspection. Posterior distribution is calculated by combining current inspection result and the prior distribution.

There are many approaches for predicting crack propagation from current measurements. To examine the effect of the prognosis model, we selected four cases of possible prognosis. First, we select a case of perfect prognosis where we know the exact crack propagation model with accurate parameters. Second case is when our prognosis model is accurate, but the parameters are uncertain. The third case is the same as the second case, but we use a least square fit instead of Monte Carlo simulation. Finally, we model a case where we have a simplistic failure prediction model, not based on any physics, but fitting a quartic polynomial to past measurements and extrapolating it. The comparison of accuracy is in Table 2.

Table 2: Comparison of accuracy with 10000 MCS

| | Estimated value (Mode, most probable value) | Standard deviation of estimation |
|---|---|---|
| Single inspection | 50.8 mm | 5.08 mm |
| 1. Perfect prognosis | 50.8 mm | 0.98 mm |
| 2. With uncertainty of parameters | 50.8 mm | 1.48 mm |
| 3. Least square fit of Paris law prognosis | 50.6 mm | 1.55 mm |
| 4. Data-driven (quartic polynomial) Least squares | 50.5 mm | 2.72 mm |

**Archival publications (published) during reporting period:**

1. A. Coppe, R. T. Haftka, N. H. Kim, and P. Ramu, Optimization of distribution parameters for estimating probability of crack detection, 12th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Victoria, British Columbia, Canada, 10-12 September, 2008.
2. A. Coppe, R. T. Haftka, N. H. Kim, C. Bes, A statistical model for estimating probability of crack detection, International Conference on Prognostics and Health Management (PHM), Denver, CO, 6-9 October, 2008.
3. J. An, R. T. Haftka, N. H. Kim, F. G. Yuan, B. M. Kwak, Bayesian approach for structural health monitoring--application to migration technique, US-Korea Workshop on Structural Health Monitoring, 31 May - 3 June, 2008.
4. G. Li, F. G. Yuan, R. T. Haftka, and N. H. Kim, “Image Segmentation of Damage in Integrated Structural Health Monitoring,” 2008 Aviation Safety technical Conference, Denver, October, 2008.
5. A. Coppe, R. T. Haftka, N. H. Kim, and F. G. Yuan, “Reducing Uncertainty in Damage Growth Properties by Structural Health Monitoring,” Annual Conference of the Prognostics and Health Management Society, 2009, CO., Denver, September, 2009.
6. A. Coppe, R. T. Haftka, N. H. Kim, and F. G. Yuan, Statistical Characterization of Damage Propagation Properties in Structural Health Monitoring, 11th AIAA Non-Deterministic Approaches Conference, Palm Spring, CA, 4-7 May, 2009.
7. J. An, R. T. Haftka, N. H. Kim, and F. G. Yuan, B. M. Kwak, “Compensation for Decay of Signal Strength in Damage Detection by Ultrasonic Imaging: Application to Migration Technique,” SDM Conference, 2009.

8. G. Li, F. G. Yuan, R. Haftka, and N. H. Kim, "Bayesian Segmentation for Damage Image using MRF Prior," *Proceedings of SPIE*, San Diego, April, 2009.
9. G. Li, F. G. Yuan, R. Haftka, and N. H. Kim, "Bayesian based Image Segmentation for Damage Quantification," In preparation, 2010.
10. G. Li, F. G. Yuan, R. Haftka, and N. H. Kim, "Probabilistic Damage Qualification and Structural Prognosis," In preparation, 2010.
11. J. An, R. T. Haftka, N. H. Kim, F. G. Yuan, B. M. Kwak, H. Sohn, and C. M. Yeum, "Experimental Study on Identifying Cracks of Increasing Size using Ultrasonic Excitation," Structural Health Monitoring, Accepted, 2011.
12. J. An, R. T. Haftka, and N. H. Kim, "Improving Diagnosis from Past Prognosis in Structural Health Monitoring," 13th AIAA Non-Deterministic Approaches Conference, Denver, CA, 4-7 April, 2011.

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Mr. Gang Li (PhD expected in August, 2009)
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